Classification of Winter Road Surface Conditions based on Continuous Friction Measurement

F. Feng & L. Fu
University of Waterloo
Waterloo, Ontario, Canada
f3feng@uwaterloo.ca
lfu@uwaterloo.ca

M. Perchanok
Ontario Ministry of Transportation
St. Catharines, Ontario, Canada
Max.Perchanok@ontario.ca

Abstract

Real time monitoring of road surface conditions during and after winter snowstorms is a critical requirement for efficient snow/ice combat operations. Although roadside reporting by road maintenance staff is still in use, especially in North America, latest sensor and information technologies, such as RWIS and web cams, have afforded new opportunities for improved road condition monitoring. Meanwhile, continuous friction measurement has been used for a long time for winter road maintenance performance measurement in some other countries. Although continuous friction measurement can provide road contaminant information with large continuous spatial coverage, inferring road surface contaminants based on mean friction only is particularly challenging as different types of contaminants could correspond to a similar level of friction.

In this research, we have developed a series of nested road surface condition classification models based on continuous friction measurement. Additional to mean friction value, new variables from probability density pattern, like variance and skewness, and from spectral density pattern of continuous friction measurement are included in the classification models. As these new variables can reflect spatial distribution patterns of snow cover along the road from different theoretical views, including them into the classifiers can improve the fitness and discriminating power of the models. The analysis was based on a set of field data collected by the Ministry of Transportation Ontario, including concurrent observations of temperature, video images of surface state and friction.

KEYWORDS

WINTER ROAD MAINTENANCE/PERFORMANCE MEASUREMENT/FRICTION /LOGISTIC REGRESSION/ROAD SURFACE CONDITION CLASSIFICATION

1. INTRODUCTION

Continuous and reliable monitoring of road surface conditions is essential for effective winter road maintenance. Quick detection of and response to snow and icy conditions can minimize the risk of collision and the effect on traffic. One of the major objectives of winter road maintenance is to bring the road surface to a safe state within a reasonable amount of time after a storm event ends. A safe state is characterized as being in a bare condition without snow/ice. This maintenance objective is called Bare Pavement (BP) recovery policy and is widely used in North America. Bare pavement status and snow depth/coverage can be reported by maintenance or quality assurance personnel based on periodic visual inspection during and after snowstorms. The main drawback of this performance measurement method is lack of objectivity and repeatability.

Friction based maintenance standards represent an alternative to BP standards with the intention of addressing the drawbacks of the later [1, 8, 11, 15]. For the last decade, there are more and more discussions on the feasibility and benefits of adopting friction based maintenance policy in the US and Canada [8, 1, 11]. Some empirical studies have found significant correlation between snow coverage and friction level [4, 12]. Some other studies tried to discriminate road surface conditions with different modeling approaches based on continuous friction measurements [2, 4, 12, 13].

Despite the increased interest in developing friction based performance measurement system for winter road maintenance, a number of issues still remain, which hinder its wide adoption in North America and around the world. When the friction measurement devices are standardized, the mapping between friction measurement ranges and road surface conditions (RSC) can be established. Most of friction based maintenance standards are based on this mapping relationship and use the observed mean friction level to estimate the RSC [3, 5, 9, 10].

The first issue with almost all existing RSC-friction mapping scheme is that the friction levels may overlap for different RSCs. This makes it difficult to reliably identify the nature of pavement contaminants solely based on friction measurements. Secondly, a lot of factors related to road surface, contaminant and tire, which may be hard to observe, measure or control, affect the friction measurement and cause more uncertainty when directly mapping mean friction levels to RSC's [6, 14]. These two issues suggest there is a need for further research to build more powerful friction-based RSC estimation models using other explanatory variables in addition to mean friction level; and it is preferable that the RSC estimation model can address the uncertainty nature of this estimation problem.

In [12], Perchanok (2002) suggested that certain probability density parameters of friction measurements, which reflected the spatial distribution patterns of snow cover, could be used to improve the discrimination power of the classifying model. Variance and skewness are two such parameters recommended by this study. As suggested by [12], [4] used probability density parameters of continuous friction measurement (CFM), specifically skewness and variance, with mean friction to calibrate a series of logistic regression models to discriminate RSC with different snow coverage. The results confirmed that adding meaningful probability density parameters can enhance the discrimination power of the logit classifiers. In [2], CFM were treated as a time series and their spectral power patterns associated with different RSCs, including bare dry, bare wet, thin wet snow, partially snow covered and fully snow covered were investigated. Information provided by the spectral powers of CFM alone can provide reliable estimation on snow coverage level and its physical distribution on the road. Specifically:

1) As the source of high-frequency power of CFM is mainly from bare pavement, the less the snow coverage, the higher the high-frequency power of CFM. Therefore, high-frequency power of mostly-snow-covered condition is the lowest, bare dry and wet conditions highest.

2) As the source of low-frequency power of CFM is mainly from the alternation of snow and bare pavement along the longitudinal direction of the measured lane, the partially snow covered condition would produce higher low-frequency power of CFM. Both bare condition and mostly-snow covered condition are lack of this alternation and thus produce much lower low-frequency power.

3) Mostly snow covered condition has lowest power at all spectral ranges. And it is hard to discriminate bare dry and bare wet conditions sole by spectral powers.

It was suggested that probability density and spectral density parameters extracted from CFM both reflected the spatial distribution patterns of snow cover along the road [2]. Their physical meanings could give solid inference on spatial variations of RSC along a maintenance route resulting from snowfall and other processes such as plowing and salting, traffic, wind-born drifting, and melting.

2. DATA COLLECTION

Data used in this study were collected on a section of Highway 417 with a total length of around 40 km in eastern Ontario. Friction data were collected using a fixed-slip-ratio continuous friction measurement equipment called Traction Watcher One (TWO). During data collection, the tow vehicle was operated in the driving lane with the friction device running in the left wheel track. The sampling distance was 10 meters. Friction measurements were collected during winter seasons of year 2007 and 2008. The test runs were scheduled carefully to cover different stages of the snow storms with a wide variety of snow coverage and environmental conditions.

A video camera was operated simultaneously to record the RSCs. The video images were used to determine the type of road surface contaminants at the test route. For this analysis, we classified snow conditions on the road surfaces into six types as follows:

Type 0: bare dry
Type 1: bare wet
Type 2: thin snow cover
Type 3: slushy snow cover
Type 4: partially snow cover
Type 5: mostly snow cover

3. DATA AGGREGATION

Instead of using point-wise friction measurement directly, CFMs of all test runs were aggregated by the distance of 500m. The sample mean of friction measurements (*F*) was calculated for each 500m interval. In addition, sample standard deviation (*Std*) and skewness (*Skew*) of friction measurements, were also calculated.

In addition to *STD* and *Skew*, spectral density powers for each 500m were also extracted. Within 500m, there were 50 evenly spaced CFMs collected. CFMs within each interval were treated as a time series and for the reasons discussed in [2], this time series was first-differenced and the density powers for different spectrum frequency were produced by conducting a Fourier transformation to the sample autocovariance function. Thus the CFMs were transformed from time domain to frequency domain and this transformation could give much more information than what is obtainable in time domain analysis. In this study, two spectral power parameters, namely *HighFreq* and *LowFreq*, were extracted. *LowFreq* was the mean spectral power of the frequency range 0.0~0.2 *periods/point*, and *HighFreq* the mean spectral power of 0.3~0.5 *periods/point*.

The RSC of each 500m interval was considered homogeneous and labeled with only one dominant RSC chosen from Type 0 to 5 according to the video image.

4. MODELING STRUCTURE

To efficiently discriminate the type of each 500m aggregation interval, *F* and extra parameters extracted from probability density and spectral density would all be tested in terms of their explanatory power of RSC. This is a typical classification problem and can be addressed by a number of traditional classification modeling approaches. In order to address the uncertainty nature of the problem as indicated in the Introduction part, logistic regression was chosen to be the modeling methodology in our study. A logistic regression model has the form

$$\ln \frac{p(Y=C_k)}{1-p(Y=C_k)} = \eta(X) \qquad \forall C_k \in C$$

Y: the categorical response variable Y
C: the set of states, which includes all possible discrete states of Y (in this study, the set of RSC types)
C_k: a state in C
$p(Y = C_k)$: the probability of Y in the state of $\mathrm{C_k}$
X: the explanatory variable vector of d features, i.e., $\mathrm{X} = (\mathrm{x_1}, \cdots, \mathrm{x_d})^{\mathrm{T}}$

$\eta(X)$ is a linear function describing the dependence of *Y* on the explanatory variables defined as follows:

$$\eta(X) = \beta_0 + \beta_1 x_2 + \cdots + \beta_d x_d$$

where $\beta_0, \beta_1, \cdots, \beta_d$ are model coefficients to be estimated. When some of the states are more similar to each other and thus share more common characteristics than other, the more proper classification scheme is a nested structure instead of a multinomial distribution. To identify this nested structure of the dataset of this study, the box-plot of 500m mean friction of each RSC type was shown in Figure 1.

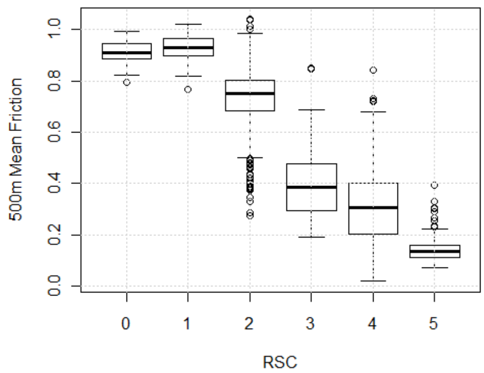

Figure 1 - Distributions of Mean Friction

Mean friction of Type 0 and 1 overlapped seriously, while both of them were within the friction range of Type 2. Type 3 and 4 overlapped a lot, and the full range of Type 5 was bracketed by Type 4. As mean friction was the most significant estimator of RSC proved by most of previous studies, the overlapping structure of mean friction levels could be treated as the reliable basis to design the nested logit model structure. According to the observations of Figure 1, the nested structure of RSC logit model was constructed as shown in Figure 2.

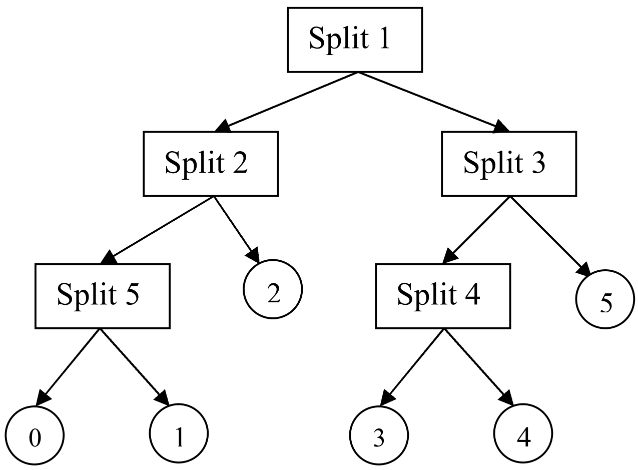

Figure 2 - Nested Logit Model Structure

As shown in Figure 2, totally five binary splits models were required to assign a 500m interval into one of six RSCs. Split 1 resided at the root of the nested tree structure and estimated the two probabilities respective to Type (0, 1, 2) and Type (3, 4, 5). Split 2 further estimated the two probabilities respective to Type (0, 1) and Type 2 assuming the RSC must be of Type 0, 1 and 2. Similarly, split 3 further estimated the two probabilities respective to Type (3, 4) and Type 5 assuming the

RSC must be of Type 3, 4 and 5. Split 4 and 5 were at the highest level of the tree structure, and respectively conducted the binary probability divisions between Type 0 and 1, Type 3 and 4.

5. MODEL CALIBRATION

A step-wise linear regression analysis was performed on observed RSC types against the potential independent variables including *F, Std, Skew, HighFreq*, *LowFreq* and their interaction terms for each split. The statistic software ***R*** was used for model calibration.

The major effect of Split 1 model was to discriminate Type 3, 4, 5 from Type 0, 1, 2. Table 1 summarizes the calibration and validation results for the logistic regression model of Split 1.

Table 1 - Calibration and Validation Results – Split 1

(a) Coefficients:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	16.335	1.742	< 2e-16
F	-27.747	2.988	< 2e-16
Skew	-6.436	2.045	0.001645
Std	-81.378	14.029	6.60e-09
LowFreq	209.286	56.901	0.000235
F * Std	105.518	24.061	1.16e-05

AIC: 264.34

(b) Calibration Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	408	28	93.58%
	1	25	407	94.21%
				93.89%

(c) Validation Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	99	5	95.19%
	1	36	525	93.58%
				93.83%

*****Class 0 indicates RSC Type 0, 1, 2**
*****Class 1 indicates RSC Type 3, 4, 5**

The following observations can be made by examining Table 1:

- Sample mean (*F*), standard deviation (*Std*) and skewness (*Skew*) of friction have a statistically significant association with this split. The negative coefficient of the mean friction level suggested that the lower the mean friction, the more likely the RSC is Type 3, 4 or 5. Adding the interaction term of *F* and *Std*, can potentially improve the model performance although this improvement is marginal
- Low-frequency spectral power (*LowFreq*) has a positive coefficient suggesting that the higher the *LowFreq*, the more like RSC is Type 3, 4 or 5. This is consistent with the relationship of *LowFreq* to RSC shown in Figure 3. As the calibration data has a large proportion of Type 3 and 4 samples, the positive

coefficient of *LowFreq* reflects this fact. A positive coefficient of *LowFreq* may not appropriate for Type 5, as it has the lowest *LowFreq*. But this doesn't affect the models discrimination power a lot, as the mean friction of Type 5 is much lower than other types, therefore the most significant parameter mean friction can rectify this issue efficiently.

- The performance of the model was tested by its "*hit rate*" in estimation. A cutoff value of 0.5 is used to define the two modeling classes, 0 and 1. When estimated probability of belonging to class 1 is equal to or greater than 0.5, and the observed class is 1, the model is considered as making a correct hit. When estimated probability of belonging to class 1 is less than 0.5, and the observed class is 0, the model is also considered as making a correct hit. Otherwise, it is considered as a missing hit. The "*hit rate*" of a group of cases was the ratio of correct hits to the total number of cases in the group. The hit rates of Split 1 model are very close for calibration and validation data sets and greater than 93%. This result suggests the root split of the nested tree structure shown in Figure 2 is appropriate.

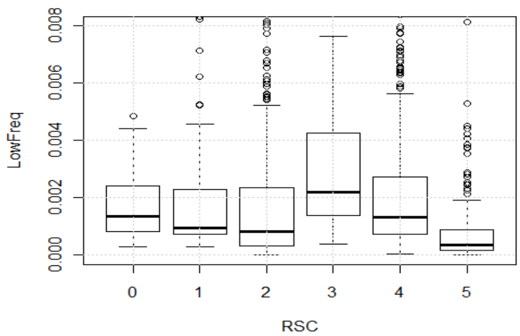

Figure 3 - Low-Frequency Spectral Power of Different RSCs

For Split 2 model, proper proportions of samples from RSC Type 0, 1 and 2 were selected in order to discriminate Type 2 from Type 0 and 1. Table 1 summarizes the calibration and validation results for the logistic regression model of Split 2.

Table 2 - Calibration and Validation Results – Split 2

(a) Coefficients:

<table>
<tr><th></th><th>Estimate</th><th>Std. Error</th><th>Pr(>|z|)</th></tr>
<tr><td>(Intercept)</td><td>33.630</td><td>5.485</td><td>8.70e-10</td></tr>
<tr><td>F</td><td>-36.583</td><td>6.080</td><td>1.78e-09</td></tr>
<tr><td>F * Std</td><td>-62.480</td><td>13.729</td><td>5.34e-06</td></tr>
<tr><td>LowFreq</td><td>431.260</td><td>139.925</td><td>0.00206</td></tr>
</table>

AIC: 81.617

(b) Calibration Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	76	6	92.68%
	1	8	80	90.91%
				91.76%

(c) Validation Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	13	0	100%
	1	22	335	93.84%
				94.05%

*****Class 0 indicates RSC Type 0, 1**
*****Class 1 indicates RSC Type 2**

The following observations can be made by examining Table 2:

- Similar to Split 1 model, the negative coefficient of the mean friction level suggested that the lower the average friction, the more likely the RSC is Type 2. The interaction term *F*Std* is significant and negatively related to the possibility of RSC is Type 2, which suggests that if *F* is held fixed, the greater the *Std* is, the possibility of belonging to Type 0 or 1 is greater. This is consistent with the *Std* distribution of Type 0, 1 and 2 shown in Figure 4.
- Low-frequency spectral power (*LowFreq*) has a positive coefficient suggesting that the higher the *LowFreq*, the more like RSC is Type 2. This is not consistent with the relationship of *LowFreq* to RSC shown in Figure 3. But in Figure 3, *LowFreq* of Type 2 has a lot of large-value outliers, which could seriously affect the calibrated coefficient and even change its sign. Those outliers might be meaningful for this split model, so the model is left as it is. Further validation will be made by examining new dataset in our future studies.
- The hit rate of the model for calibration and validation dataset are respectively greater than 91% and 94% suggesting a reliable performance of the model.

For Split 3 model, proper proportions of samples from RSC Type 3, 4 and 5 were selected in order to discriminate Type 5 from Type 3 and 4. Table 3 shows the results for the initial try of logistic regression model of Split 3.

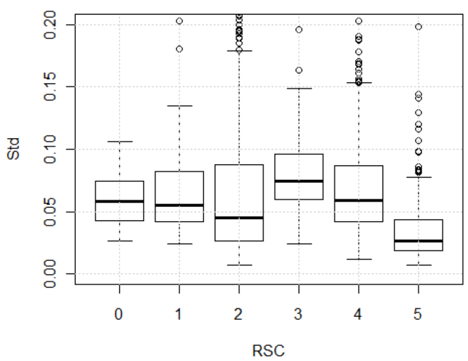

Figure 4 - 500m Aggregation Interval Friction Standard Deviation of Different RSCs

Table 3 - Initial Model for Split 3

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	4.0461	0.4699	<2e-16
F	-22.0364	2.6283	<2e-16
HighFreq	146.7908	69.0400	0.0335

AIC: 241.74

The sign of the coefficient for *F* is correct but the sign of coefficient of *HighFreq* is not consistent with the observation of *HighFreq* distribution of Type 3, 4 and 5 shown in Figure 5. So the model was recalibrated by overlooking the *HighFreq* term. Table 4 summarizes the final results of the modeling and validation.

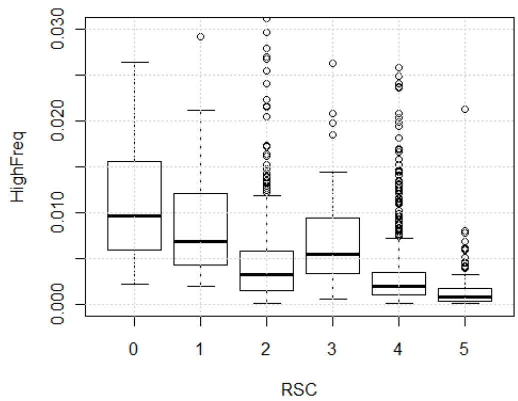

Figure 5 - High-Frequency Spectral Power of Different RSCs

Table 4 - Calibration and Validation Results – Split 3

(a) Coefficients:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	5.1592	0.6903	7.80e-14
F	-26.6955	3.7944	1.99e-12
F * Std	103.3920	34.0962	0.00243
Std	-21.4591	9.9093	0.03035

AIC: 242.03

(b) Calibration Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	143	27	84.12%
	1	21	112	84.21%
				84.16%

(c) Validation Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	510	137	78.83%
	1	4	39	90.70%
				79.57%

*****Class 0 indicates RSC Type 3, 4**
*****Class 1 indicates RSC Type 5**

The following observations can be made by examining Table 4:

- The negative coefficient of the mean friction level suggested that the lower the average friction, the more likely the RSC is Type 5.
- The negative coefficient of the standard deviation suggested that the lower the standard deviation, the more likely the RSC is Type 5, which is consistent with observations of Figure 4.
- The interaction term *F*Std* is significant and positively related to the possibility of RSC is Type 5, which causes some difficulties to explain. Again this doesn't affect the models discrimination power a lot, as the mean friction of Type 5 is much lower than Type 3 and 4, therefore the most significant parameter mean friction can rectify this issue efficiently. So leaving this interaction term as it is will not significantly affect the performance of the model, which is confirmed by the high hit rates of the model shown in Table 4 (b) and (c)

- The hit rate of the model for calibration and validation dataset are respectively greater than 84% and 79% suggesting a reliable performance of the model. The AIC is 242.03 which is not significantly higher than that of the model shown in Table 3, whose AIC is 241.74, so overlooking the *HighFreq* term almost has no impact on model fitness.

For Split 4 model, proper proportions of samples from RSC Type 3 and 4 were selected in order to discriminate Type 4 from Type 3. Table 5 summarizes the model coefficients and validation results.

Table 5 - Calibration and Validation Results – Split 4

(a) Coefficients:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	1.5951	0.3322	1.58e-06
HighFreq	-244.3735	64.4537	0.000150

AIC: 135.85

(b) Calibration Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	19	20	48.72%
	1	9	76	89.41%
				76.61%

(c) Validation Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	2	6	25%
	1	77	608	88.76%
				88.02%

*****Class 0 indicates RSC Type 3**
*****Class 1 indicates RSC Type 4**

In the Split 4 model, which discriminate Type 3 and 4, mean friction is not significant any more. *HighFreq* is significant and has a negative coefficient, which is consistent with the observation shown in Figure 5. Usually, Type 4 has higher snow coverage than Type 3, therefore *HighFreq* power should be lower, which is suggested by [2]. This fact is confirmed by this Split 4 model. The hit rate of the model for calibration and validation dataset are respectively greater than 76% and 88% suggesting a reliable performance of the model.

For Split 5 model, proper proportions of samples from RSC Type 0 and 1 were selected in order to discriminate Type 1 from Type 0. Due to unknown reason, the mean friction of Type 1 is greater than Type 0, which is not a reliable phenomenon and not consistent with historical studies. This may be caused by some immeasurable or unobservable factors affecting friction measurement. So the mean friction is not considered as an explanatory variable in the model calibration process. Table 6 summarizes the model coefficients and validation results.

Table 6 - Calibration and Validation Results – Split 5

(a) Coefficients:

	Estimate	Std. Error	Pr(>|z|)
(Intercept)	0.6505	0.4543	0.1522

LowFreq	520.2671	225.4552	0.0210
HighFreq	-129.6003	59.2006	0.0286

AIC: 83.05

(b) Calibration Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	11	15	42.37%
	1	3	35	92.11%
				71.88%

(C) Validation Data:

		Estimated Class		
		0	1	Hit Rate
Observed Class	0	4	6	40%
	1	7	14	66.67%
				58.06%

*****Class 0 indicates RSC Type 0**
*****Class 1 indicates RSC Type 1**

In the model for Split 5, which discriminate Type 0 and 1, mean friction is not used due to measuring error. *LowFreq* and *HighFreq* are both significant. As indicated by [2], it was really hard to discriminate bare dry and bare wet conditions by solely relying on spectral density powers, this model cannot be assumed reliable either theoretically or practically. The hit rate of the model for calibration and validation dataset are respectively greater than 71% and 58% suggesting that spectral density parameters has a potential ability to discriminate RSCs.

6. CONCLUSION AND FUTURE RESEARCH

This research has investigated the feasibility of automatically discriminating road surface conditions based on continuous friction measurement. A set of nested logit models was developed to determine the probability that a road surface is in six road surface condition types. This nested structured model consisted of five binary logistic regression models, which considered independent variables from probability density and spectral density in addition to mean friction level.

Friction measurements and other data were aggregated at a given distance so that aggregate attributes such as variance, skewness and spectral density parameters of friction could also be incorporated. Out of all five models, three had probability parameters proved significant, and four had spectral density parameters proved significant. Two models could solely use spectral density terms to get high-quality estimation of RSC without considering mean friction at all, which confirmed the implications of our previous study [2]. However, further research is needed before these results can be generalized. Future research should focus on validating the proposed modeling techniques using data from other maintenance routes or highway of different classes.

7. ACKNOWLEDGEMENTS

This research was supported by Ministry of Ontario (MTO) and NSERC. All data were collected and prepared by MTO Eastern Region Contracts Office.

REFERENCES

[1] Al-Qadi, I.L., Loulizi, A., Flintsch, G.W., Roosevelt, D.S., Decker, R., Wambold, J.C. & Nixon, W.A. (2002). *Feasibility of Using Friction Indicators to Improve Winter Maintenance Operations and Mobility*: National Cooperative Highway Research Program, p. 151 p.

[2] Feng, F. & Fu, L. (2009). Spectral Analysis of Continuous Friction Measurements for Winter Road Surface Condition Discrimination. In *Transportation Research Board 88th Annual Meeting.* Transportation Research Board.

[3] FNRA (2001). *Winter Maintenance Policy in Finland*: Finnish National Road Administration.

[4] Fu, L., Feng, F. & Perchanok, M.S. (2008). Probabilistic Models for Discriminating Road Surface Conditions Based on Friction Measurements. In *Transportation Research Board 87th Annual Meeting.* Transportation Research Board.

[5] Katko, K. (1993). *Goals and Methods of Winter Maintenance in Finland*: Transportation Research Board, p. p. 8-11.

[6] Kummer, H.W. (1996). Unified Theory of Rubber and Tire Friction. In *Engineering Research Bulletin* Pennsylvania: The Pennsylvania State University, Department of Mechanical Engineering.

[7] Mc-Cullagh, P. & Nelder, J.A. (1999). *Generalized Linear Models,* (Second edn): Chapman & Hall/CRC.

[8] Nixon, W.A. (1998). *Friction as A Tool for Winter Maintenance*: Iowa State University, Ames, p. p. 86-89.

[9] Nordstrom, O. (1998). *Development and Validation of BV14, A New Twin Track Fixed Slip Friction Tester for Winter Road Maintenance Monitoring in Sweden*: PTRC Education and Research Services Limited, p. p. 741-753.

[10] Öberg, G. & Gregersen, N.P. (1991). MINSALT : an experiment with unsalted road in Västerbotten county. *VTI meddelande 636*.

[11] Perchanok, M.S. (1998). *Friction Based Quality Assurance Measures for Snow Clearing Operations*: PTRC Education and Research Services Limited, p. p. 199-208.

[12] Perchanok, M.S. (2002). *Patchiness of Snow Cover and Its Relation to Quality Assurance in Winter Operations*: World Road Association - PIARC, p. 10p.

[13] Perchanok, M.S. (2008). An Approach to Terrain Classification to Improve Road Condition Forecasts of Maintenance Decision Support Systems. In *Fourth National Conference on Surface Transportation Weather; Seventh International Symposium on Snow Removal and Ice Control Technology.* Transportation Research Board. pp. pp 337-350.

[14] Sandberg, U. (1997). Influence of Road Surface Texture on Traffic Characteristics Related to Environment, Economy and Safety. Linköping: Swedish National Road and Transport Research Institute.

[15] Wallman, C.-G. & Åström, H. (2001). Friction Measurement Methods and the Correlation between Road Friction and Traffic Safety: A Literature Review.